Evaluating Spatial Characteristics of Upper-Limb Movements from EMG Signals

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Abstract—**Stroke is a major cause of disability, usually causing hemiplegic damage on the motor abilities of the patient. Stroke rehabilitation seeks restoring normal motion on the affected limb. However, 'normality' of movements is usually assessed by clinical and functional tests, without considering how the motor system responds to therapy. We hypothesized that electromyographic (EMG) recordings could provide useful information for evaluating the outcome of rehabilitation from a neuromuscular perspective. Four healthy subjects were asked to perform 14 different functional movements simulating the action of reaching over a table. Each movement was defined according to the starting and target positions that the subject had to connect using linear trajectories. Bipolar recordings of EMG signals were taken from biceps and triceps muscles, and spectral and temporal characteristics were extracted for each movement. Using pattern recognition techniques we found that only two EMG channels were sufficient to accurately determine the spatial characteristics of motor activity: movement direction, length and execution zone. Our results suggest that muscles may fire in a patterned way depending on the specific characteristics of the movement and that EMG signals may codify such detailed information. These findings may be of great value to quantitatively assess post-stroke rehabilitation and to compare the neuromuscular activity of the affected and unaffected limbs, from a physiological perspective. Furthermore, disturbed movements could be characterized in terms of the muscle function to identify, which is the spatial characteristic that fails, e.g. movement direction, and guide personalized rehabilitation to enhance the training of such characteristic.**

Keywords—**EMG, movement spatial characteristics, pattern recognition, stroke rehabilitation, upper-limb.**

I. Introduction

Stroke is considered a leading cause of disability [1], mostly related to upper limb impairment, since the recovery is slow and often limited [2], [3]. Quantitative evaluation of motor functions is essential to determine therapeutic efficiency and guide personalized rehabilitation. However, current available methods are subjective and do not reveal the behavior of the motor system during rehabilitation [4].

Movement execution entails symmetric processes of the two upper limbs [5]. Therefore, the impairment (or recovery) level of a patient could be assessed by comparing the motor function of the healthy and impaired limbs. Given that the EMG patterns of contractions producing different movements are distinct [6], we hypothesized that EMG signals may provide useful parameters to characterize motor improvement.

To prove such hypothesis we defined 14 different movements simulating reaching, since it is an important motor component of the daily life activities, and usually one of the basis of post-stroke rehabilitation [7]; and we classified them according to their spatial characteristics (direction, length and execution zone) using pattern recognition techniques with a set of EMG features.

II. Methods

A. Data acquisition

Four healthy subjects (three males, one female) participated in this study. All subjects were 27-35 years old and right handed. Electromyographyc (EMG) signals were recorded using two pairs of circular disposable Ag-AgCl electrodes (1 cm in diameter, 1.5 cm inter-electrode distance; Foam electrode 50/PK – EL501, Biopac Systems Inc.) from the biceps brachii (C1) and triceps brachii (C2) of the right arm according to published guidelines [8]. A fifth reference electrode was placed at the wrist. EMG data were collected through the EMG 100C acquisition system (BIOPAC Systems, Inc.) at a sampling rate of 1000 Hz and a gain of 500.

B. Experimental Protocol

Subjects sat down in front of a table were a white grid indicated different target positions (Fig 1). The height of the chair was adjusted so that the elbow described an angle of 90º when placing the forearm on the table. The subjects were instructed to perform 14 different functional movements with their right hand by following linear trajectories. Each movement simulates the action of reaching and entails the proximal and distal upper-limb muscles, which are essential to perform daily life activities. Each subject repeated each movement 30 times. So at all, 420 EMG recordings were analyzed for each subject. All contractions began or ended with the subject's arm by the side in a comfortable neutral position. No constraints were imposed on the force or velocity of the contraction, except that the subject was asked not to drag the arm along the table and to be consistent in reproducing the linear trajectory specified in each case. EMG signals were manually segmented from movement onset (simultaneous with the auditory trigger) to the instant the limb-movement stopped after reaching the target position. Subjects were allowed to rest for 2-3 min between movements to avoid muscular and mental fatigue.

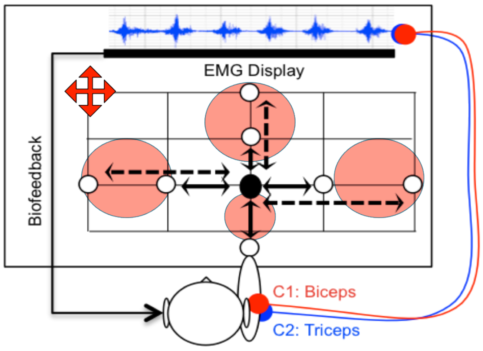

Fig. 1 Experimental protocol. Subjects were instructed to perform 14 functional movements with their right arm simulating reaching on a table. Movements were defined on a grid indicating the positions to reach (circles) by linear back and forth trajectories (arrows) starting and ending in the neutral position (black circle). EMG features from biceps and triceps were used to identify patterns of movement direction (red arrows), length (dotted vs continuous arrows) and execution zone (red circles).

C. Data Preprocessing and Feature extraction

EMG signals were digitally filtered with fourth-order bidirectional Butterworth highpass (20 Hz) and lowpass (400 Hz) filters to remove movement artifacts and the high-frequency noise. A Notch filter was used to remove 50 Hz interference and mean was also subtracted. A third differential channel, C3, was offline computed by subtracting the signals of channels 1 and 2.

The feature set used to characterize the EMG data for movement classification was composed of the total power spectral density (PSD), mean PSD, mean and median frequency, root mean square (RMS), RMS ratio, signal variance and the feature set proposed by Hudgins *et al.* [6]. PSD was estimated using Burg's method; RMS ratio was defined as the ratio between the maximum absolute value and the RMS of the signal; the Hudgins' feature set was computed in the first 5 segments of 50 ms of each contraction. At all, 37 features were computed in each channel (C1: Biceps Brachii, C2: Triceps Brachii, C3: C1-C2). Additionally, estimations of Magnitude Squared Coherence (MSC) and cross-PSD (cPSD) between channel 1 (Biceps Brachii) and channel 2 (Triceps Brachii) were included. MSC indicates how well two signals correspond to each frequency.

D. Classification

Contractions were labeled according to their directions (ToUp, ToRight, ToDown, ToLeft); length (Long, Short); and the execution zone where they were performed in respect to the neutral position (Up, Right, Down, Left) (Fig 1). That is, each contraction was given three labels to allow applying pattern recognition techniques to the spatial characteristics of the 14 movement types separately.

Support vector machines (SVMs) were implemented using radial basis function (RBF) kernels [9] to classify contractions according to each of their three labels. The selection of gamma and C-parameters of the RBF was optimized to obtain maximum classification accuracy. Then, a 5-fold cross-validation was carried out with the optimized classifier. The accuracy of each classification was the percentage of correctly classified contractions. For each subject the performance was computed as the averaged accuracy of the five folds. The overall performance was evaluated as the mean accuracy across all subjects.

III. Results

A. Qualitative characterization of muscle activity patterns

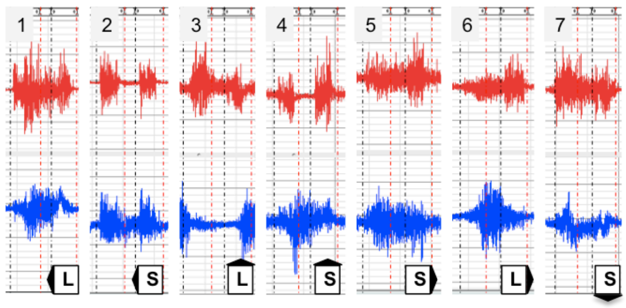

Fig. 2 Examples of the EMG signal for the seven pairs of movements (Subject 4). Red signals: biceps brachii, Blue signals: triceps brachii. L: Long Movements, S: Short Movements. Black arrows indicate the direction of the movement. Black dotted lines indicate movement onset, red dotted lines indicate movement end.

Fig. 2 shows the EMG recordings of the biceps brachii and triceps brachii muscles while performing the 7 pairs of back and forth movements. The EMG signal and activation pattern shape differs with each movement type. Similarly, the temporal coordination between the two muscles was different. For example, when performing movements upwards (plot 3), triceps brachii is activated prior to the recruitment of muscle fibers on biceps brachii. Conversely, for downward movements (plot 7) the activation of biceps muscle occurs before activity is detected on the triceps.

B. Model selection

Akaike's Information Criterion (AIC) was used to select the most relevant EMG features determining a particular spatial characteristic of the movement (direction, length or execution zone). Feature selection was carried out iteratively, so that in the first step the AIC of the model built with the full set of features was calculated. In the next iteration a feature was left out and if the AIC of the reduced model diminished, then the feature was discarded. This process was repeated for every feature until the most informative (reduced) feature set was found for each movement characteristic.When comparing the three reduced feature sets we found that there was not a consensus on the features able to discriminate simultaneously the three spatial characteristics. Therefore, characterizing completely each contraction requires the complete feature set.

C. Detection of Movement Spatial Characteristics

Pattern recognition analysis revealed that the feature set and the proposed SVM classifier were able to accurately predict the direction, length and execution zone of the movement from EMG. Overall classification accuracies were 84.27%, 93.80% and 87.93%, respectively.

Table 1 Subject-specific classification accuracy of movement spatial characteristics.

	Subject #			
Spatial Characteristics	S1	S2	S3	S4
Movement Direction				
ToUp	0.96	0.89	0.90	0.95
ToRight	0.85	0.87	0.65	0.93
ToDown	0.84	0.81	0.68	0.95
ToLeft	0.85	0.87	0.71	0.94
Movement Length				
Short	0.98	0.96	0.86	0.98
Long	0.95	0.95	0.88	0.96
Execution Zone				
Up	0.89	0.92	0.82	0.98
Right	0.90	0.84	0.75	1.00
Down	0.97	0.92	0.81	0.95
Left	0.96	0.94	0.80	0.96

Table I contains subject-specific classification accuracies for the categories of the three movement characteristics. In general, we were able to classify the categories within each movement characteristic with accuracies above 85%, except for subject 3 for which classification performances were especially low comparing to the rest of the subjects. We did not find any category that was specially easy/tough to characterize: the patterns we found allowed recognizing specific categories with similar accuracy.

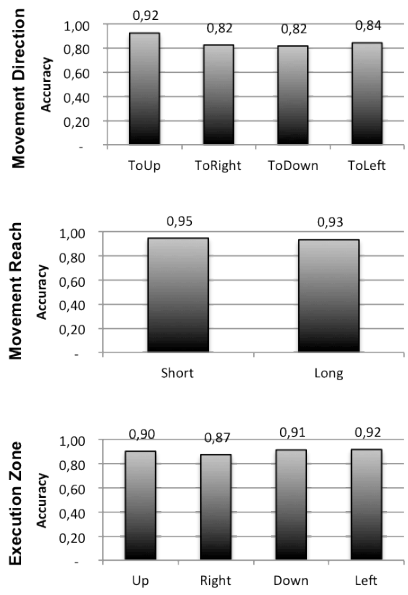

Fig. 3 Overall class-by-class classification accuracy of movement spatial characteristics from EMG

The accuracy with which upward movements (ToUp) were detected was significantly higher (92%) than other movement directions (82-84%) (Fig.3). In contrast, we identified different categories from movement length and execution zone with similar accuracy: Short and long movements were correctly characterized in 95% and 93% of the cases, while movements performed in the space located Up, Right, Down or Left of the neutral positions were in 90%, 87%, 91% and 92% of the cases respectively.

IV. Discusion

This study demonstrates that EMG signal codifies spatial characteristics of movements that can be detected with high accuracy applying pattern recognition techniques. In particular, we have successfully applied SVMs to decode the direction, length and execution zone of 14 different planar movements that simulate reaching. At present, the outcome of rehabilitation is assessed using subjective and time consuming functional tests and kinematic analysis of movements [10], [11]. However a recent study showed that kinematic parameters do not reveal the behavior of the motor system, during rehabilitation [12]. Thus, this information may be very useful to assess rehabilitation from the perspective of the motor system and provide further understanding on the neuromuscular mechanisms behind functional recovery.

Quantitative evaluation of the rehabilitation is necessary to estimate therapeutic efficiency. Muscle activity is similar on both sides of upper limbs when performing the same movement [5]. Therefore, comparing the EMG features proposed in this study between the impaired and healthy limb in hemiplegic stroke patients may facilitate quantitative assessment. Besides, in the clinical practice the use of EMG is limited to analyze muscle activation patterns and evaluate muscle strength [13]. However, our study shows that EMG may provide much more information about spatial characteristics of movements, such as direction or length. Therefore, our system may enhance the potential of EMG and simplify the complementary instrumentation currently used to evaluate the kinematic aspects of movements. Furthermore, given that these parameters indicate specific motor skills, they may guide custom rehabilitation by indicating which aspects of motor recovery (e.g. movement direction) should be reinforced with rehabilitation.

Similar studies have been carried out using high density EMG (> 60 channels) [14]–[16]. Our approach is especially attractive because it achieves high accuracies using only 2 EMG channels, which makes the system easy and confortable to implement. Furthermore, unlike these studies, our system is able to discriminate the spatial characteristics from highly related movements that involve the same set of joints. Thus it is likely that the accuracy of the system will increase substantially when performing movements that combine joints and muscles differently. In addition, no averaging is needed for movement characterization, which allows assessing each contraction individually.

V. CONCLUSIONS

This study demonstrates that EMG codifies spatial characteristics of movements, such as direction, length or the execution zone. The set of EMG features proposed allows obtaining high accuracies in the spatial characterization of individual contractions corresponding to 14 different reaching movements by pattern recognition techniques. Thus, we provide a new framework to quantify the outcome of stroke rehabilitation directly from the perspective of motor system and guide personalized therapy to reinforce recovery on individual motor problems.

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